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Understanding Automobile Ownership Behavior of Low-Income Households: How Behavioral Differences May Influence Transportation Policy.

Alissa D. Gardenhire
Doctoral Candidate, Urban Planning
Harvard University
Perkins Hall #206
35 Oxford Street
Cambridge, MA 02138
Telephone: (617) 493-4900
E-mail: adgarden@fas.harvard.edu

M William Sermons, Ph.D.
Assistant Professor of Civil and Environmental Engineering
University of Maryland
1179 Glenn Martin Hall
College Park, MD 20742
Telephone: (301) 405-2046
E-mail: sermons@eng.umd.edu

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Abstract

Modeling household automobile ownership choices is a key component of travel behavior research and of travel demand analysis and forecasting. Typically, auto ownership models have not addressed the differences in automobile ownership behavior for different population segments. Low-income households are a population segment whose auto ownership behavior is particularly relevant for public policy concerning household mobility. When making automobile ownership choices, it is expected that all households, regardless of income, consider their own mobility needs, purchasing power, availability of alternate modes, and various characteristics of the urban environment. How do low-income households evaluate these factors differently than non-poor households, and how can these differences impact traditional transportation policies aimed at helping the poor? This research proposes to examine this question. Automobile ownership models of residential location choice are estimated for samples of poor and non-poor households from the 1995 Nationwide Personal Transportation Survey. The analysis tests whether the automobile ownership choice behavior of low-income households is significantly different from that of middle- and upper-income households. The empirical analysis involves estimation of ordered choice models of automobile ownership and involves a criterion-based segmentation search methodology to explore the influence of race, gender, and life-cycle status on automobile ownership choice behavior. The results reveal that factors such as household income and residential density affect poor households' automobile ownership behavior differently than they do non-poor households' behavior. Specifically, poor households convert income into automobiles at a higher rate and convert larger adult household size into automobiles at a lower rate than non-poor households. The implication of these findings on public policy concerning the mobility of low-income households, including welfare-to-work policy, is discussed.

Introduction

Modeling household automobile ownership choices is a key component of travel behavior research and of travel-demand analysis and forecasting; however, very few modeling efforts have examined whether factors such as income or transit access differently influence the auto ownership decisions of different segments of the population.

One population segment whose automobile ownership behavior is of particular interest is low-income households. Low-income households have been the focus of many public policy efforts aimed at improving their mobility. Transportation policies and programs have focused on improving the mobility of low-income people; but they have primarily worked to move the unemployed poor to work sites or areas of high employment density. The vast majority of these publicly funded solutions have been transit-based. Low-income households have been identified in the literature to be more likely than non-poor households to be without cars and to make up a large proportion of transit-dependent households. They face myriad mobility related disadvantages because of this disproportionate dependency on non-auto travel.

Although some qualitative research has been done and many transportation policies made, the question of whether poor household consider their own mobility needs, purchasing power, availability of alternate modes, and various characteristics of the urban environment differently than non-poor household has been virtually ignored in automobile ownership applications. It is clear that households, regardless of income, consider their own mobility needs, purchasing power, availability of transit, and the characteristics of the urban environment as they make choices about automobile ownership. The literature identifies income as perhaps the most important determinant of household automobile ownership. However, the automobile ownership choice models in the past have not examined whether the automobile-ownership decision for poor households differs from that of non-poor households in ways that extend beyond differences in purchasing power. Until now, it was not known whether factors identified to influence car ownership decisions were identical for poor and non-poor households or which factors, if they do indeed differ, are most important to poor households. Any differences that do exist may be obscured in traditional models that do not examine the automobile ownership behavior of poor households separately.

This research evaluates the automobile-ownership choice behavior of American households using the 1995 Nationwide Personal Transportation Survey. It tests whether the automobile-ownership choice behavior of low-income households is significantly different from that of middle- and upper-income households. This empirical analysis involves estimation of ordered choice models of automobile ownership and involves a criterion-based segmentation search methodology to explore the influence of race, gender, and life-cycle status on automobile ownership choice behavior. Specific issues addressed include an assessment of the importance of income, residential density and transit access in the automobile ownership decisions of low-income households.

Previous Research

Automobile-ownership models are abundant in the transportation literature. Many researchers have attempted to develop models to explain household automobile ownership decisions. Most studies include the following three variables as the dominant influences on household automobile ownership: household income, residential density, and access to transit. Household income has been identified as the most important influencing factor. However, few studies have explicitly examined automobile ownership behavior for potential differences in automobile ownership behavior among poor and non-poor households.

Behavioral differences in automobile ownership among demographic segments have been identified in the literature. For example, Lerman and Ben-Akiva (1976) find that households make very different automobile ownership choices depending on their socio-economic and life-cycle status. Gardenhire (1998) found significant residual differences among socio-economic and demographic groups in evaluating household likeliness of being without an automobile within the 1995 NPTS sample. Controlling for the influence of income, residential location, and access to transit, households headed by blacks, Hispanics, females, single adults, and young people were substantially more likely to be without automobiles than households not in those categories.

See studies by Dargay and Gately (1995), Geinzer, Daly, and Pol (1981), Golob (1989), Goodwin, (1988), Holtzclaw (1994), Kain, Fauth, and Zax (1978), Kidder and Saltzman (1972), Kitamura (1989), Kockelman (1996), Meyer, et. al. (1965), and Meyer and Gomez-Ibanez (1981), for more on factors that influence car ownership. See Schimek (1996) for analysis that makes use of the National Personal Transportation Survey for automobile ownership analysis.

This research employs a criterion-based segmentation search methodology to identify heterogeneity across households. Criterion-based segmentation methodologies, such as classification and regression trees (CART) and automated interaction detection (AID), have been used by transportation researchers to identify the influence of household demographic changes on travel behavior (Washington and Wolf, 1997; Strambi and van de Bilt, 1998; Vaughn, Speckman and Pas, 1997). This research makes use of a segmentation search methodology that was developed by Wilmot (1983) to identify heterogeneity in urban mode choice models and employed by Sermons (1998) for identifying taste heterogeneity in residential location choice models. This research represents the only known application of the Wilmot (1983) approach to an automobile-ownership application.

Behavioral and Segmentation Variables

The variables used in the statistical analysis have been classified as either behavioral or segmentation variables. Behavioral variables are those variables that have been shown in the literature to explain automobile ownership behavior and for which there is a clear behavioral explanation for their inclusion. These variables are:

- Household income,
- Residential and employment density,
- Access to transit variables, and
- Household composition and life-cycle variables (including employment status).

The eleven variables that are listed in Appendix 1 are the behavioral variables. It should be noted that these variables alone represent a complete automobile ownership model specification similar to those that have been included in automobile ownership applications in the literature.

The other classification of variables included in this analysis is segmentation variables. These are household socio-demographic variables that have been found by researchers to have some influence on auto ownership behavior, but for which their influence is unclear. These variables include:

- Poverty,
- Gender of the household head,
- Household race,
- Single head status, and
- Retirement status of household head.

Poverty status is the dominant variable of interest, as it is on the differences between the poor households and the sampled non-poor households that this research focuses. The other segmentation variables are employed as potential variables in the segmentation search procedure 1) to identify those that significantly influence auto ownership behavior of poor and/or non-poor households, and 2) to identify which behavioral coefficients exhibit sensitivity to the identified segmentation variables. This second point represents the important advantage of this research approach over those that control for demographic variables by simply adding dummy variables. The dummy variable approach allows the identification of an overall bias toward higher or lower auto ownership of households with some characteristic, while the approach used in this research allows a more complete representation of the influence of the household characteristics on automobile ownership behavior. For example, in previous research by

Gardenhire(1998), the inclusion of dummy variables revealed that poor households were much more likely to be without automobiles than non-poor households. The methodology employed in this research allows us to find the trade-offs made by non-poor households that account for the difference.

Model and Model Results

The empirical automobile ownership models estimated for this research are ordered probit models and were estimated using *LIMDEP* 7.0. The dependent variable in each model is number of automobiles. The dependent variable is truncated at 3+ because there is a relatively small number of households with more than three automobiles, especially among poor households, which is our focus population.

Interpreting the results of the ordered probit estimation is similar to interpreting regression analysis, but the resulting "regression function" is really an index function that indicates increasing likelihood of auto ownership for increasing values of the index. Another difference is that the index function alone does not predict auto ownership directly as the OLS regression function does. A set of n-1 threshold parameters, where n is the number of auto owner ship categories (4 in this case), are estimated to relate the continuous index function to discrete auto ownership levels[1]. This facilitates classification into discrete categories without requiring a fixed linear relationship between the index function and the auto ownership level (the use of an OLS regression function for discrete

[1] LIMDEP constrains the first threshold parameter (i.e. the one that delineates zero car households from 1 car households) to a value of zero; therefore, only 2 (or n-2) threshold parameters as shown for each model.

classification would generally require an assumption of a linear relationship between the regression function and the discrete categories).

The household data came from the 1995 National Personal Transportation Survey (NPTS). The 1995 NPTS includes 42,033 households, but just under 5,000 were needed for this analysis. The sample used for this analysis included all 2493 poor households (based on the U.S. Official Poverty Threshold) that reported income and all other important household characteristics. Since the focus is on identifying differences between the poor and non-poor auto-ownership behavior, a comparable number of non-poor households (2500) were selected randomly among the non-poor households. Including a much larger number of the available non-poor households in the sample may have resulted in bias in the segmentation analysis.

The variables that enter the index function for all of the models are defined in appendix 1 and are the same variables used in all of the auto ownership models. In addition, the following segmentation variables were used for the market segmentation analysis:

1. Gender of households head (male vs. female),
2. Number of adults in household (1 vs. 2+),
3. Race (White vs. Non-white)
4. Employment status (retired vs. non-retired)

All of the segmentation variables are categorical variables with two levels. The segmentation variables were used in a segmentation search procedure to identify behaviorally different market segments among the poor and non-poor households respectively. The search procedure is similar to the procedure developed by Wilmot

(1983) for multinomial logit models and is applied here to ordered automobile ownership probit models. The procedure was applied twice: once for the poor households and another time for the non-poor households. The procedure works as follows:

1. Estimate a pooled model using all of the poor or all of the non-poor observations.
2. Split the households into binary segments using each of the segmentation variables. This results in four pairs of segments (one for each of the segmentation variables) the first time through the procedure.
3. Estimate ordered probit auto ownership models for each pair of segments.
4. Of the splits that reject equality of parameters between segments, the split that accounts for the largest likelihood improvement is selected. The split made here will create two new pooled models that serve as the starting point for the next iteration of splits.
5. Repeat steps 2, 3 and 4 on the newly-created segments until all splits are exhausted, until further splits create insufficient sample sizes for estimation, or until none of the splits result in rejection of the parameter equality hypothesis.

Results

The auto ownership models estimated for the population of poor households, model 1, and the population of non-poor households, model 2, respectively are shown in Table 1. Each of the models provides reasonable results, with most of the model parameters being significant and of the appropriate sign; however, the number of children in the household is found not to be a significant indicator of household automobile ownership for either poor or non-poor households. Among the household composition variables (i.e. head worker dummy, number of workers in the household, number of adults in the household, number of children in the household), only the adult household population variables are indicative of auto ownership level. Another result that applies to both poor and non-poor households is that rail transit accessibility appears to be twice as important as accessibility to other transit modes in describing household auto ownership.

In addition to presenting each of the models, Table 1 facilitates comparisons between the poor and non-poor models. The last column in the table provides t-test statistics that test the hypothesis that each of the poor and non-poor household parameters are identical. The t-values indicate that 6 of the 11 index function parameters as well as both of the threshold parameters are significantly different across the two populations, an indication that auto ownership behavior is very different for the two populations. One of the differences is that the adult household composition parameters (head worker dummy, the number of additional workers in the household, and the number of non-working adults) are all significantly larger in the non-poor household model as compared with the poor household model. This indicates that non-poor households with a given number of adults are more likely than poor households with the same number of adults to exhibit higher levels of automobile ownership. Another difference is that poor households appear to translate additional income into additional automobiles at a much faster rate (more than twice as quickly) than non-poor households. Similarly, poor households appear to be more sensitive than non-poor households to residential density when making automobile ownership decisions. Above and beyond the behavior captured by the index function parameters, the constants indicate that non-poor households have an additional overall bias toward auto ownership, a bias that poor households do not exhibit. The fact that the constant for the poor households is not significantly different from zero suggests that the variables in the index function pretty adequately explain the poor households' auto ownership behavior. Lastly, the larger threshold parameters for the non-poor households relative to poor households creates a larger index range within which households are predicted to own 1 or 2 automobiles; this larger range results in most of the non-poor households being classified as having 1 or 2 automobiles.

In addition to the index function parameter comparisons, transferability tests were performed to determine the extent to which the poor household model reflects the behavior of non-poor households and vice-versa. The transfer index was developed and defined by Wilmot and Koppelman (1983) and is shown here:

$$TI_{Poor}(b_{Non-Poor}) = \frac{LL_{Poor}(b_{Non-Poor}) - LL_{Poor}(MS_{Poor})}{LL_{Poor}(b_{Poor}) - LL_{Poor}(MS_{Poor})}$$

$$TI_{Non-Poor}(b_{Poor}) = \frac{LL_{Non-Poor}(b_{Poor}) - LL_{Non-Poor}(MS_{Non-Poor})}{LL_{Non-Poor}(b_{Non-Poor}) - LL_{Non-Poor}(MS_{Non-Poor})}$$

$TI_{Poor}(b_{Non-Poor})$ describes the degree to which the log-likelihood of the transferred non-poor model exceeds the market shares model relative to the improvement provided by the model developed for poor households. Likewise, $TI_{Non-Poor}(b_{Poor})$ describes the degree to which the log-likelihood of the transferred poor model exceeds the market shares model relative to the improvement provided by the model developed for non-poor households. $TI_{Poor}(b_{Non\text{-}Poor})$ has a value of *-0.40,* a result that suggests that the transferred model (non-poor model) is worse than the market shares model. This is likely due to the bias of the non-poor model toward predicting ownership of 1 or 2 automobiles and the contrasting likelihood of autolessness of poor households. $TI_{Non[Poor}(b_{Poor})$ has a value of *0.72,* which when compared to $TI_{Poor}(b_{Non\text{-}Poor})$ suggests that the poor model is a much better predictor of non-poor auto ownership behavior than vice versa. If the transfer index were 1, it would indicate that the poor model was identical to the non-poor model, while a value of 0 would indicate that the poor model was identical to the non-poor market shares model. A value of 0.72 indicates that the poor model is much better than the market shares model at explaining non-poor households' auto-ownership behavior, but not nearly as good as the non-poor model.

Segmentation Results

The segmentation search procedure resulted in the splits shown in Figure 1 and the models shown in Table 2 for the poor households and the splits shown in Figure 2 and the models shown in Table 3 for the non-poor households. In each table, the un-segmented model is repeated in the first column with the models for each of the identified segments shown in the remaining columns. The results indicate that there is a fair amount of heterogeneity that is not captured by the un-segmented models. One common result is that gender of the household head is identified as the primary segmentation variable among both poor and non-poor households; the models indicate a bias toward auto ownership among the households headed by males as compared with those headed by females. Except for the gender split, the segmentation schemes suggested for the poor households are very different from those suggested for the non-poor households. Among poor female-headed households, number of adults in the household provides a significant split. Among non-poor male headed households, employment status (retired vs. not retired) is a significant split. Among non-poor female-headed households, race is the identified split.

That there are more segments identified among the non-poor population indicates that there is more heterogeneity among the non-poor households. This result is not particularly surprising, as it was previously noted that the bias captured in model 2 for the non-poor households suggested that the non-poor households' auto ownership behavior was not adequately by the behavioral variables alone.

One of the three segments identified by the segmentation process is poor single, female headed households, a population that receives lots of attention in policy discussions about poverty. The households in this segment appear to be particularly sensitive to rail transit accessibility in their auto-ownership decisions.

Summary of Results

In an effort to summarize the important results, the following highlights are identified:

- By dividing the sample by income, into poor and non-poor segments, a picture of the differences in automobile ownership behavior among the segments has been revealed.
- The results show that poor and non-poor households do indeed exhibit different automobile ownership choice behavior.

- Non-poor households exhibit a bias toward higher auto ownership, but poor households convert income to automobiles at twice the rate of non-poor households.
- Poor household automobile ownership behavior is more sensitive to residential density than non-poor household behavior.
- Poor households respond to transit availability to the same degree that non-poor households do.

The segmentation results reveal the following:

- The first split for both segments is along gender lines. Households headed by females have different automobile ownership behavior than those headed by males regardless of income segment, with females owning fewer cars than males in each group.
- Among poor households, the female-headed households further segment into one and two adult households, while male headed households do not. There is no additional segmentation among the poor households.

Discussion and Conclusion

The results show that poor households do indeed exhibit different automobile ownership behavior than non-poor households, a fact that until now has been inadequately addressed in auto ownership modeling research. For instance, the model shows that poor households convert income to automobiles at twice the rate of non-poor households. It also shows that poor and non-poor household automobile ownership is affected to about the same degree by presence of transit. We not only see that the factors identified in the literature on automobile ownership impact low-income households to a different degree than non-poor households, but also that within poor and non-poor population segments further behavioral differences exist.

These results confirm the need for transportation planners and policy makers to consider the mobility needs of the poor using models that specifically identify the behavior of the poor households as different than that of the non-poor households where appropriate. Simply assuming that models estimated for the whole population are directly transferable to low-income households is inappropriate.

Understanding the automobile ownership behavior of low-income households is interesting for its own sake, but more so for how it can inform planners and policy makers about low-income mobility. Understanding this behavior will assist in gaining a greater understanding of the mobility challenges low-income people face. Mobility, not car ownership, is the true issue. Welfare-to-work programs predominantly focus on transit-based solutions to the mobility problems of program participants (see 1998 American Public Transit Association report "Welfare-to-Work Survey and Summary Report"). However, these solutions may neither be optimal nor true long-term solutions to the mobility issues that welfare recipients face. Long-term solutions that allow these participants to be both independent and to optimize their work force, educational, personal, familial, and social opportunities are car-based solutions. Car ownership for this small segment of the population, that is otherwise work-ready, will provide these families with the same set of opportunities, allowing them to make the same choices and access the same resources as non-poor families.

Depending on the priorities of policy makers with regard to low-income mobility, real solutions to the mobility challenges of the poor are attainable. However, in order to address the real mobility needs of low-income people, policy makers must move away from their sole dependence on transit-based solutions. Traditional transit-based policies may not work for today's poor, mobility disadvantaged household. In light of changing commute patterns that are not well served by public transit and considering our result that indicates that poor household auto ownership is not more affected by transit availability than non-poor household auto ownership, planners and policymakers must consider non-transit solutions to mobility issues of the poor. O'Regan and Quigley (1998) make this point when they advocate government policy consider auto ownership opportunities for the poor in the form of secured loan programs, leasing schemes, or revolving credit arrangements.

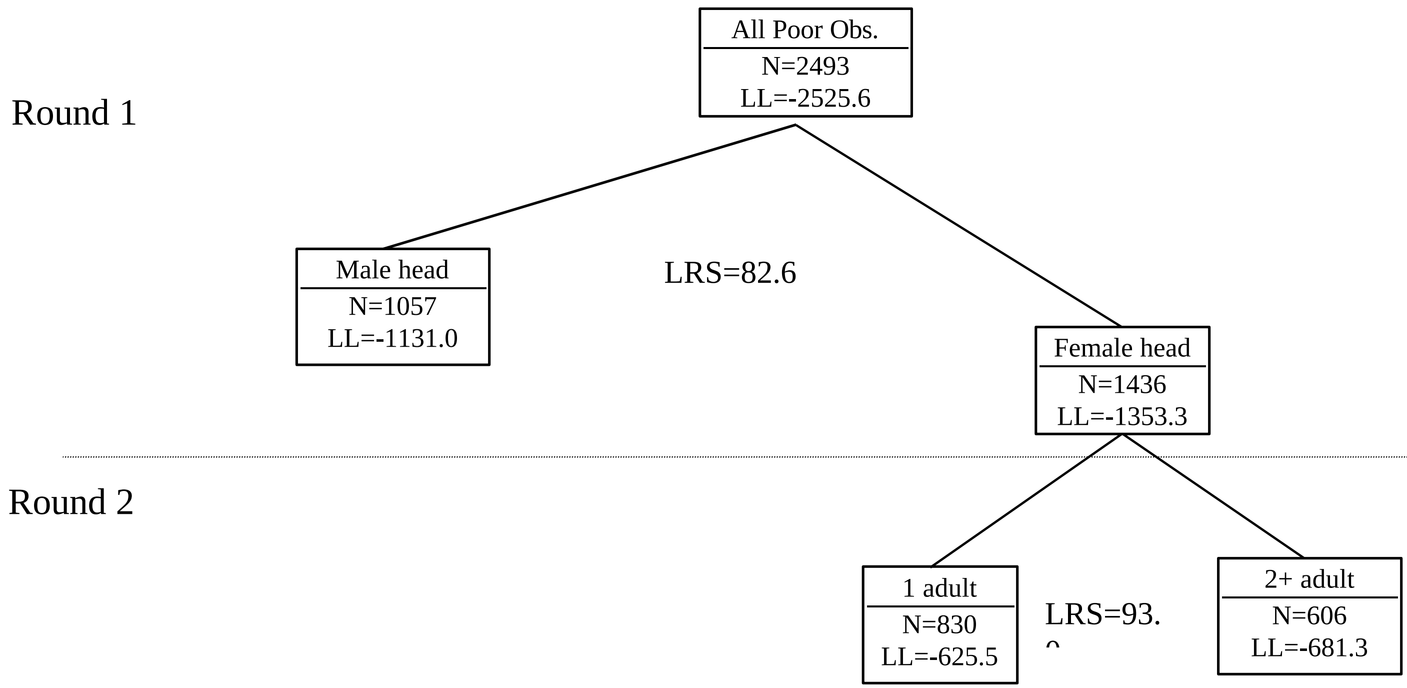
Transportation policymakers have the ability to decide where money goes for improving the mobility of the poor. Our results show that poor households themselves are pouring dollars into car ownership at a surprisingly high rate. This finding identifies how large a priority car ownership is for these households that face the constraints of limited incomes. Of course, transportation planners and policymakers should continue to provide high quality standard and specialized transit services to low-income people who are unable to drive, but they should also seriously consider and pursue non-transit solutions to address the mobility issues of the poor.

TABLE 1 Auto Ownership Models: Poor vs. Non-Poor Households

Variable name	*Model 1 (coefficient)*	*Model 2 (coefficient)*	*Model 1 – Model 2 t-value*
INDEX FUNCTION			
Constant	**-.0658**	**0.291****	**-3.0**
Head worker dummy	**0.854****	**1.13****	**-2.9**
Number of workers in hh (excluding head)	**0.763****	**1.25****	**-10.1**
Number of adults in hh (excluding head)	**0.533****	**0.884****	**-6.2**
Number of children in household	-0.0174	0.0364	-1.7
Household income ($ 000)	**0.0247****	**0.00884****	**2.4**
Access to transit dummy	-0.151*	-0.191**	0.5
Access to rail transit dummy	-0.209**	-0.189**	-0.2
Distance to nearest transit stop (miles)	0.0401**	0.0269*	0.7
Residential density (units/sq. mile)	**-0.000130****	**-0.0000742****	**-2.3**
Employment density (jobs/sq. mile)	-0.0000430*	-0.0000602**	0.6
THRESHOLD PARAMETERS FOR INDEX			
μ(1)	**1.56****	**1.90****	**-6.8**
μ(2)	**2.78****	**3.74****	**-15.1**
GOODNESS OF FIT			
Number of Observations	2493	2500	
LL(c)	-3016.2	-2875.2	
LL(β)	-2525.6	-2159.0	
% correct predictions	54%	68%	

* significant at .05 level
** significant at .01 level

Model 1 – All poor households (no segmentation)
Model 2 – All non-poor households (no segmentation)



LRS is the Likelihood Ratio Statistic = - 2(LL_{pooled}-$LL_{segment\ 1}$-$LL_{segment\ 2}$)

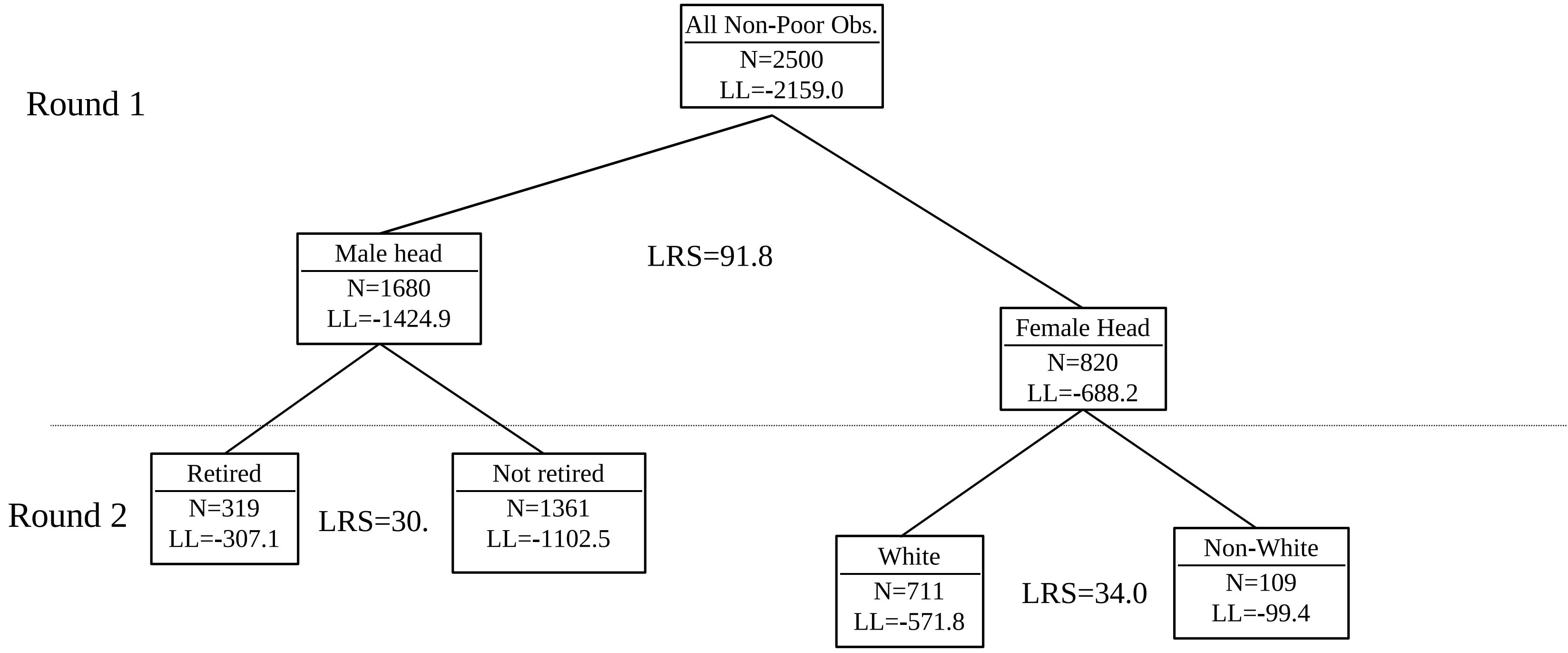
Figure 1. Splits Made During Criterion Based Segmentation of Poor Households

TABLE 2 Auto Ownership Models for Poor Households

Variable name	*Model 1*	*Model 3*	*Model 4*	*Model 5*
INDEX FUNCTION				
Constant	-.0658	0.424**	0.152	0.398*
Head worker dummy	0.854**	0.731**	.565**	0.423**
Number of workers in hh (excluding head)	0.763**	0.760**		0.434**
Number of adults in hh (excluding head)	0.533**	0.505**		0.134
Number of children in household	-0.0174	0.0137	.0197	-0.0530
Household income ($ 000)	0.0247**	-0.00129	.0490	0.0395**
Access to transit dummy	-0.151*	-0.156	-0.208	-0.0326
Access to rail transit dummy	-0.209**	-0.188	-0.308*	-0.169
Distance to nearest transit stop (miles)	0.0401**	0.0309	0.0242	0.0502
Residential density (units/sq. mile)	-0.000130**	-0.000147**	-0.0000917**	-0.000118**
Employment density (jobs/sq. mile)	-0.0000430*	-0.0000458	-0.0000490	-0.0000545
THRESHOLD PARAMETERS FOR INDEX				
$\mu(1)$	1.56**	1.53**	2.17**	1.28**
$\mu(2)$	2.78**	2.76**	3.18**	2.65**
GOODNESS OF FIT				
Number of Observations	2493	1057	830	606
LL(c)	-3016.2	-1329.0	-695.3	-746.8
LL(β)	-2525.6	-1131.0	-625.5	-681.3
% correct predictions	54%	53%	65%	48%

* significant at .05 level
** significant at .01 level

Model 1 – All poor households (no segmentation)
Model 3 – Households with male head
Model 4 – Households with female head & 1 adult in household
Model 5 – Households with female head & 2 or more adults in household



LRS is the Likelihood Ratio Statistic = $-2(LL_{pooled} - LL_{segment\ 1} - LL_{segment\ 2})$

Figure 2. Splits Made During Criterion Based Segmentation of Non-Poor Households

TABLE 3 Auto Ownership Models for Non-Poor Households

Variable name	*Model 2*	*Model 6*	*Model 7*	*Model 8*	*Model 9*
INDEX FUNCTION					
Constant	0.291**	0.828**	0.753**	-0.339	0.167
Head worker dummy	1.13**	0.888**	1.06**	1.59**	0.675
Number of workers in hh (excluding head)	1.25**	1.14**	1.14**	1.60**	0.938**
Number of adults in hh (excluding head)	0.884**	0.492**	0.674**	1.22**	0.904**
Number of children in household	0.0364		0.0499	0.0548	0.0105
Household income ($ 000)	0.00884**	0.0133**	0.00615**	0.0114**	0.0121
Access to transit dummy	-0.191**	-0.258	-0.158*	-0.187	-0.199
Access to rail transit dummy	-0.189**	-0.250	-0.119	-0.342*	0.116
Distance to nearest transit stop (miles)	0.0269*	-0.00202	0.0287	0.0335	-0.0102
Residential density (units/sq. mile)	-0.0000742**	0.00000887	-0.000117**	-0.0000388	-0.0000665
Employment density (jobs/sq. mile)	-0.0000602**	-0.0000934	-0.0000228	-0.0000551	-0.000121
THRESHOLD PARAMETERS FOR INDEX					
$\mu(1)$	1.90**	1.72**	1.86**	2.34**	2.00**
$\mu(2)$	3.74**	3.37**	3.87**	4.14**	3.53**
GOODNESS OF FIT					
Number of Observations	2500	319	1361	711	109
LL(c)	-2875.2	-361.7	-1400.2	-838.5	-125.1
LL(β)	-2159.0	-307.1	-1102.5	-571.8	-99.4
% correct predictions	68%	57%	68%	69%	60%

* significant at .05 level; ** significant at .01 level

Model 2 – All non-poor households (no segmentation)
Model 6 – Households with male head & retired
Model 7 – Households with male head & not retired
Model 8 – Households with female head & white
Model 9 – Households with female head & non-white

APPENDIX 1. Variable definitions

Variable name	Definition
Constant	1 for all households.
Head worker dummy	1 if head (NPTS reference person) is employed full time , 0 otherwise
Number of workers in hh (excluding head)	Number of workers other than the head employed full time
Number of adults in hh (excluding head)	Number of non-working adults other than the head in the household
Number of children in household	Number of children in the household.
Household income	Annual household income in ($1000)
Access to transit dummy	1 if some form of transit is available to members of the household, 0 otherwise
Access to rail transit dummy	1 if rail transit is available to members of the households, 0 otherwise
Distance to nearest transit stop (miles)	NPTS approximated distance to nearest transit stop (any transit mode)
Residential density (units/sq. mile)	Number of residential units per square mile in the household's census tract/block group?
Employment density (jobs/mile)	Number of jobs per square mile in the household's census trace/block group?

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